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ABSTRACT

In an attempt to bridge the gap between academic understanding and practical business use, the Box-Jenkins technique of time series analysis for forecasting future events is presented with a minimum of mathematical notation. The method is presented in three stages: a discussion of traditional forecasting techniques, focusing on traditional techniques that relate to the Box-Jenkins model; a presentation of the key characteristics of the Box-Jenkins model; and a detailed demonstration of the method's steps. A discussion of the technical requirements needed to use the model, its cost versus that of other forecasting methods, and the potential areas of its application conclude the paper. The mathematical rationale is appended. (Author/DW)

FORECASTING - A SYSTEMATIC MODELING METHODOLOGY

by

Vincent A. Mabert

and

Robert C. Radcliffe

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Forecasting - A Systematic Modeling Methodology

(Draft - Not for Quotation)

(Revised August 1974)

by

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Abstract

This article describes a rather new approach to forecasting, the Box-Jenkins methodology. The basic steps of the technique are presented as well as a discussion of why the financial manager should get better forecasts using this methodology.

Introduction

This paper presents an introductory description and application of the Box-Jenkins (BJ) technique of time series analysis for forecasting future events. The BJ method represents a rather new and sophisticated approach to time series analysis that academicians have been using in recent years. However, little application has been found in the business community to date. This has been mainly due to its technical nature; precluding ease of understanding by the average practioner.

While academic studies using the BJ technique have shown it to be a highly successful short term forecasting tool, we are aware of only a few companies who are presently using the technique. The principal user appears to be American Telephone and Telegraph. It has been applied to forecasts of telephone installations, electric power generation and sales, industrial company sales and common stock price moves.[1]

We attempt to bridge this gap in understanding between the academic and business community, by describing the BJ technique with a minimum of mathematical notation. By moving the reader through three stages, a basic understanding of this technique is attained. The first stage discusses traditional forecasting techniques; focusing on their basic structure and their relationship to the BJ model. Stage two introduces the basic Box-Jenkins model, with it's key characteristics. In stage three, a detailed example is given to demonstrate the steps an analyst moves through in applying this methodology. Columbus and Southern Ohio Electric Company monthly power generation provides the basis for this illustrative case study.

The paper concludes with a discussion of the technical or skill level requirements to work with the methodology, its cost versus other forecasting methods, and potential areas of application. For the interested reader, the appendix contains a mathematical development of material covered in the body of the paper.

Traditional Forecasting Approaches

In general, there are three basic approaches to forecasting:

1. Qualitative Judgments
2. Quantitative Models - Considering External Variables
3. Quantitative Models - Time Series.

Qualitative forecasts usually rely upon individual experience and intuition mixed with market surveys. The principal benefits of such forecasts grow out of the fact that historical data is often not available for quantitative modeling and such forecasts can be quickly prepared. There are a number of disadvantages in using qualitative judgments, however. First, the manager might easily forget to consider the influence of certain factors which could have been identified and accounted for in an organized quantitative model. Second, forecasts could well be influenced by the mood of the forecaster; such that the forecaster might make two different forecasts when presented with the same facts at two different times.[2] Finally, it is difficult for many individuals to assign an indication of the probable variation around expected demand. Most managers simply are not trained to think in terms of standard deviation and statistical measurement of risk.

In order to eliminate such problems inherent in qualitative forecasts, an increasing number of firms have begun utilizing quantitative forecast techniques.[3] Quantitative techniques which rely upon a set of external

(exogenous) factors to explain the variable being forecast are often quite useful - in particular when making long range forecasts. Least squares regression analysis represents one such technique that falls into this classification. However, such forecasts have two shortcomings. They lead to good forecasts only as long as the relationship between the dependent variable and explanatory variables remains constant. This is certainly a major difficulty in periods of rapid socio-economic change. Secondly, they require an extensive investigation of potential explanatory factors. This is a time-consuming and costly process which should only be entrusted to those well trained in statistical analysis.

The third approach to forecasting utilizes past trends in the variable being forecast to estimate the future. Such techniques are referred to as time series analysis. They are most useful when the manager is faced with relatively short planning horizons - ranging from a few weeks to a few years - and the need for new forecasts is repetitive.

Historically, the two approaches utilized to examine time series have been autoregression [4] and moving average (including exponential smoothing) [2][10] models. In an autoregressive model, the present level of the forecast variable is said to be a function of prior levels of the variable plus some unforeseen random shock which occurs in the present period. In a moving average model, the present level of the forecasted variable is said to be a function of previous unforeseen random shocks which have occurred plus the unforeseen shock which occurs in the present period. Notice the subtle difference which exists between the two techniques.

The two techniques will not lead to the same set of forecast values since each model is based upon different modeling strategies. An auto-regressive model represents the current observation of a series as a linear combination of previous values that explain the current observation. Thus, the value of the prior obser ions indicate the appropriate forecast. On the other hand, a moving average model tracks upon prior forecast errors to indicate the appropriate forecast.

A significant problem could arise if the series is modeled using one or the other of the two techniques when, in fact, it actually follows some mixture of the two processes. In most situations there is no *a priori* way of telling which process is the most appropriate. The methodology suggested by Box and Jenkins [1] represents a systematic approach to modeling and forecasting discrete time series using a combined auto-regressive-moving average model and should generally lead to the best forecasts available.

There are two basic reasons why the BJ methodology leads to better forecasts than traditional forecasting methods and thus should be preferred to them. First, using traditional approaches the forecaster would more or less arbitrarily select a specific forecasting model. For example, in estimating seasonal cash collections he might decide to use an exponential smoothing model when in fact some form of a mixed autoregressive-moving average model would be more preferable. The methodology proposed by Box and Jenkins begins with a broad generalized model called an Auto-regressive Integrated Moving Average Model (ARIMA), which is inclusive of all possible separate model combinations of moving average and autoregressive

models. Using this broad model the forecaster rationally backs into an appropriate model. He does not arbitrarily decide to pick, say, an auto-regressive function but instead eliminates inappropriate models until he is left with the most suitable one. Second, the specific form of a given model which is to be used has traditionally been the result of a trial-and-error procedure with a good deal of experience and intuitive judgment thrown in. Box and Jenkins, however, present a rational, structured approach to the determination of a specific model. Certainly experience and judgment must remain, but their structured approach eliminates various hit-and-miss tactics.

In the next section, the principal concepts behind the Box and Jenkins model are developed. The presentation is kept at a fairly low level and as non-quantitative as possible in the hope that non-statisticians will understand what really is going on. Those interested in a more detailed and sophisticated approach should examine (in ascending order of difficulty) the papers by Mabert and Radcliffe [7], Ferratt and Mabert [6], and Tiao and Thompson [9]. In addition, the appendix provides a more extensive and mathematical development of the model than given here.

The Basics of the Box-Jenkins Model

Let us assume that a budget director wishes to forecast cash receipts by analyzing historical patterns. The BJ technique does not attempt to analyze actual levels of the forecasted variable but, instead, to model the difference between the variable level and it's mean value. We will continue to follow this convention, such that R_t will refer not to receipts in any month t but, instead, to the difference in receipts in month t and the mean value of receipts. The ARIMA model for such

receipts can be expressed as:

ARIMA MODEL

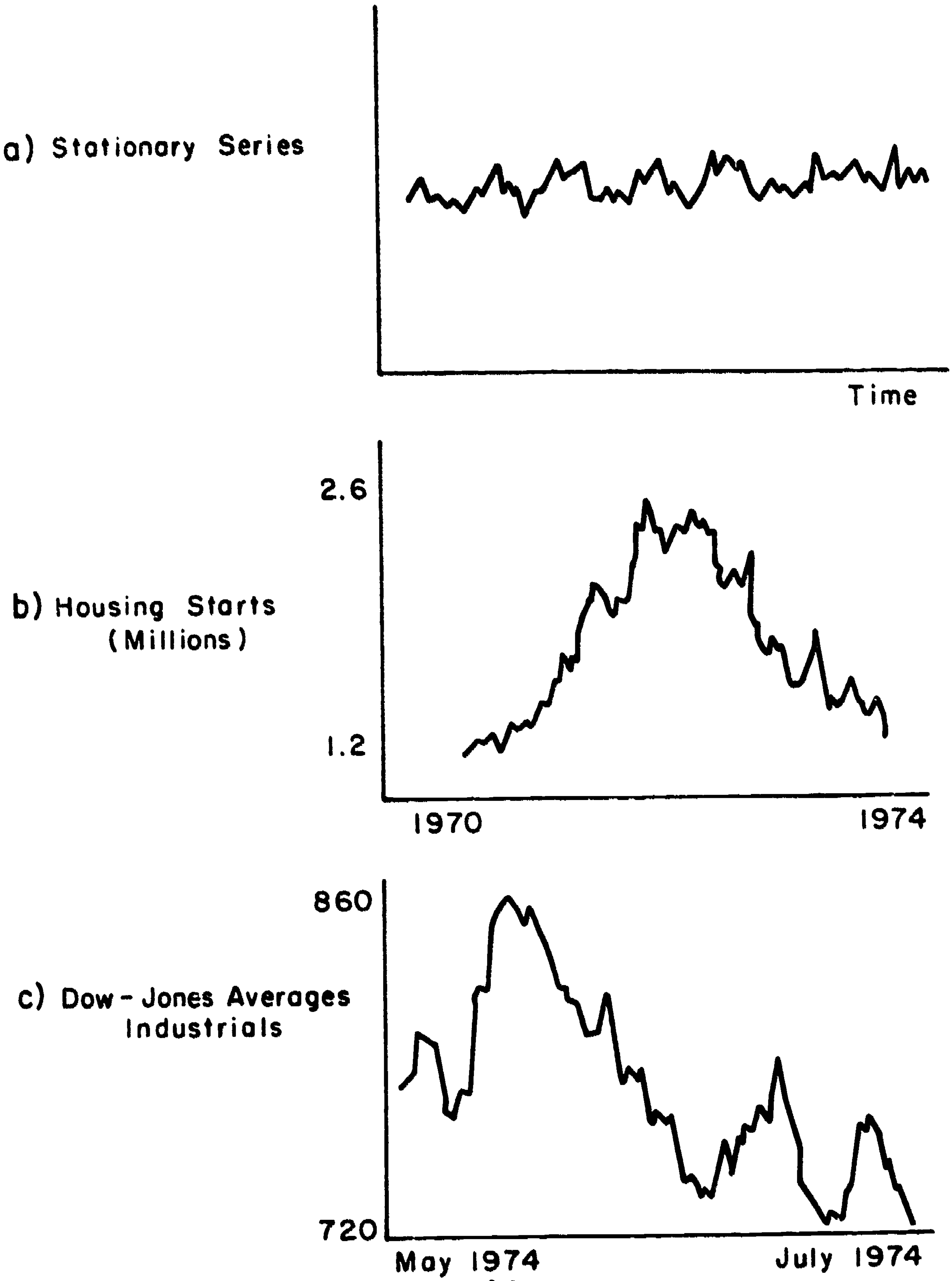
$R_t =$		Dependent Variable
	$\phi_1 R_{t-1} + \phi_2 R_{t-2} + \ldots + \phi_p R_{t-p}$	Autoregressive Portion
	$+\ \theta_o - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \ldots - \theta_q a_{t-q}$	Moving Average Portion
	$+\ a_t$ (1)	Shock Term

The ϕ's and θ's respectively represent the autoregressive and moving average coefficient values which we wish to estimate. The p and q terms represent the number of periods back which we actually model, while the a_t terms represent unforeseen random shocks occuring in period t. Finally, θ_o represents a deterministic trend constant which is usually equal to zero since most processes are dynamic and continually changing in trend.

A question may come to mind as to what a_t represents and why a negative, weight $(-\theta)$ is present in equation (1). The $a_{t-q}'s$ represents the forecast error, defined as $a_{t-q} = (R_{t-q} - \hat{R}_{t-q})$, where $(\hat{\ })$ indicates the forecasted value. The negative weights are the common nomenclature used, and is therefore employed, and the weight values need not be positive or sum to unity [p. 10, 1].

The ARIMA model of equation (1) is based upon the crucial assumption that the times series is normally distributed around some constant mean. That is to say the time series is "stationary" as illustrated in Exhibit 1a. Of course, stationary series are more the exception than the rule in most business situations due to existance of business cycles and changes in consumer preferences and desires. Examples of non-stationary series would be housing starts and stock market prices. Compare their

Exhibit 1. Common Time Series



movements as shown in Exhibits 1b and 1c with the stationary series in Exhibit 1a.

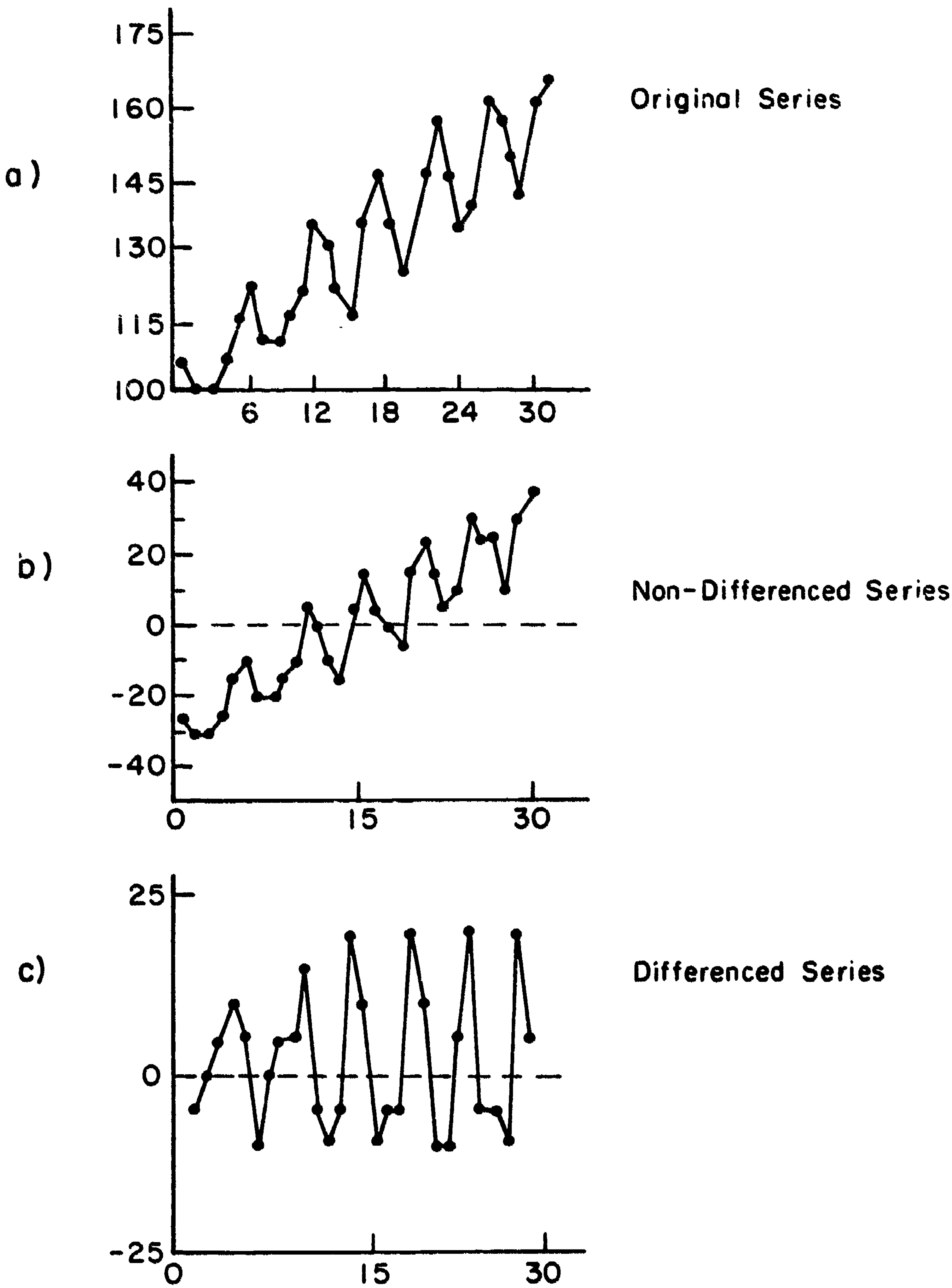
Luckily, most non-stationary series, which have changing means overtime can be easily converted into stationary ones by a simple transformation called "differencing." Using the differencing technique, one obtains the differences from a mean that changes over time. For example, assume June cash receipts, R_t, are \$5,000 and July receipts, R_{t+1}, are \$7,000. The value plotted for July is not \$7,000 but, instead, the difference between the July and June receipts of \$2,000. Such a transformation will allow us to obtain a reasonably stationary series of cash receipts, which we'll define as SR_t (stationary receipts in t). Mathematically, one would calculate SR_t as

$$SR_t = R_t - R_{t-1} \qquad (2)$$

To illustrate graphically how such a differencing procedure will transform a non-stationery series into a stationary one, examine Exhibit 2. Section a of the exhibit represents the historic values of cash receipts as plotted over time. Section b represents the plot of R_t values over time, i.e., the plot of cash receipts (from section a) minus the mean level of receipts. The non-stationarity inherent in both sections a and b is quite apparent. However, by simply taking "first differences" ($SR_t = R_t - R_{t-1}$) a reasonably stationary series is created as shown in section c. The desirability for having a stationary series is dicussed soon. It turns out to be the crux of model identification.

Now we can rewrite the cash receipts ARIMA model of equation (1) to explicitly account for the fact that we are modeling and forecasting a stationary time series, the new ARIMA differs from the first only in that

Exhibit 2. Sample Times Series



R_t is replaced by SR_t as follows:

$$SR_t = \phi_1 SR_{t-1} + \phi_2 SR_{t-2} + \ldots + \phi_p SR_{t-p} + \theta_o - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \ldots - \theta_q a_{t-q} + a_t \qquad (3)$$

Notice that the final estimated model need not include both autoregressive and moving average terms as any, or all, of the ϕ's and θ's could enter with a zero. However, the model is sufficiently general to handle all possible combinations of autoregressive and moving average terms.

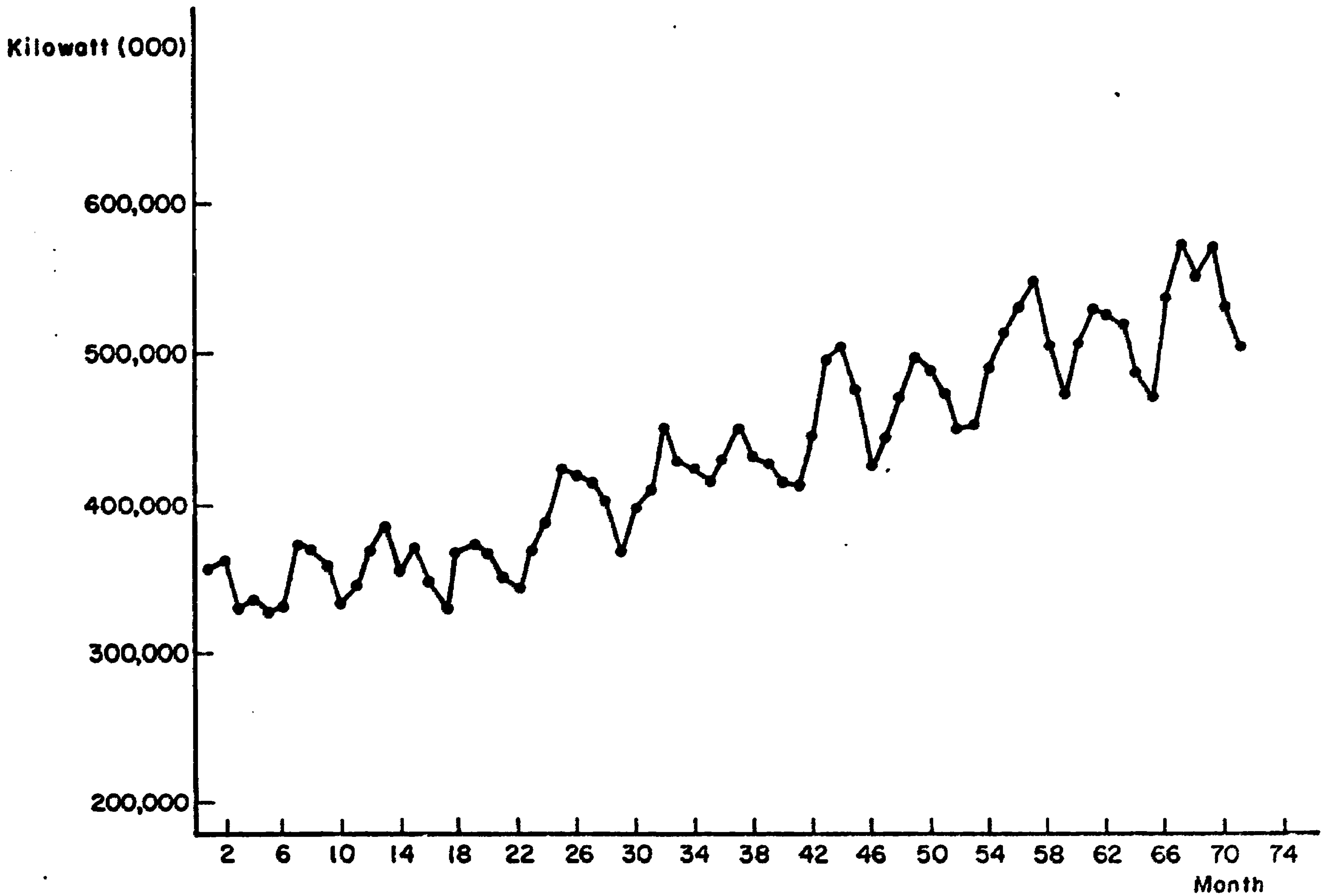
The Box-Jenkins Model Development Strategy

Based upon the stationary ARIMA model, Box and Jenkins suggest a three step iterative process to reach a satisfactory predictive model. These three steps are Identification, Estimation, and Diagnostic Checking; which we shall cover in the next section. To illustrate these three steps, Columbus and Southern Ohio Electric Company's (CSOE) monthly power generation is used as a case study.

Identification Procedure:

The first step requires the analyst to examine the time series for outliers (extreme values) and trends. If explainable outliers are present, some form of adjustment may be required by the analyst, such as substituting the average value for this extreme observation. The presence of a trend indicates the need for differencing. Exhibit 3 presents a plot of CSOE monthly kilowatt sales for a seven year period of 1965-1972. Notice that no outliers are present. However, there is a strong upward trend, punctuated with seasonal variations with increasing magnitude, occurring at twelve month intervals. This has important implications on how we can obtain a stationary series. The time series should exhibit the same level

Exhibit 3. Columbus and Southern Ohio Electric Kilowatt Sales



of variation over the whole range, which it does not. However, a simple log transformation of the original series (K_t) allows one to easily handle this issue ($K'_t = \log K_t$) and obtain a series with the proper characteristics. The presence of this trend with a seasonal fluctuation indicates that differencing is necessary to obtain a stationary series, (KWH_t). At this point the analyst would investigate both regular differencing ($KWH_t = K'_t - K'_{t-1}$) and seasonal differencing ($KWH_t = K'_t - K'_{t-12}$) to attain a stationary series. Both are investigated because we are not sure that the trend is a function of one month to the next or from one month in a year to that same month in the prior year.[4]

Determination of which differencing pattern is appropriate comes from analyzing the resulting series via the sample autocorrelation function. Just as the mean and standard deviation describe the central tendency and dispersion of the set of observations, the sample autocorrelation measures the relationship between interdependent observations; i.e., the correlation between periods. Calculating the autocorrelation for observations lagged one period apart, two periods apart, and so on to k periods apart allows the analyst the capability of inferring what the underlying data generating process is (autoregressive, moving average, ARIMA). By plotting such "sample autocorrelation coefficients" for various lags, one can begin to see the relationship which might exist between the interdependent observations. Theoretical autocorrelations for differing lags are known for each of the alternative models we might examine. One compares the actual autocorrelation values with the theoretical values for the different possible models and select that model for which the theoretical values best approximate the actual values.

Exhibit 4 depicts common patterns for different autoregressive and moving average models. Autoregressive processes have autocorrelation coefficients which start with high values and gradually decrease as the lag increase. This is illustrated in first and second order models shown in the exhibit. Moving average processes exhibit large values (spikes) that indicate the appropriate order of the model. When a mixed process is present, we cannot identify the complete model at this stage. Rather, we start with the autoregressive model indicated by the sample autocorrelations pattern and let the diagnostic step of the BJ method indicate the appropriate improvement.

Let us now examine the sample autocorrelation pattern for a "regular" (month to month) and "seasonal" (year to year) differencing of the CSOE power generation data as shown in Exhibit 5. Notice that the sample autocorrelation of the "regularly differenced" series (Exhibit 5a) exhibits neither a systematic decaying pattern nor large dominating spikes -- suggesting that a model based upon one month differencing is inappropriate. However, the "seasonally differenced" series (Exhibit 5b) suggests that a reasonable differencing scheme might have been found. In particular, the decaying pattern is indicative of an autoregressive process and the sinusoidal movement suggests that the autoregressive model be of "second order." Exhibit 4 contains a theoretic pattern for a second order autoregressive process which looks amazingly like that of the series in Exhibit 5b. Given this similarity we would originally postulate a second order autoregressive model to explain power sales in any month (KWH_t) as follows:

$$KWH_t = \phi_1 \; KWH_{t-1} + \phi_2 \; KWH_{t-2} + a_t \qquad (4)$$

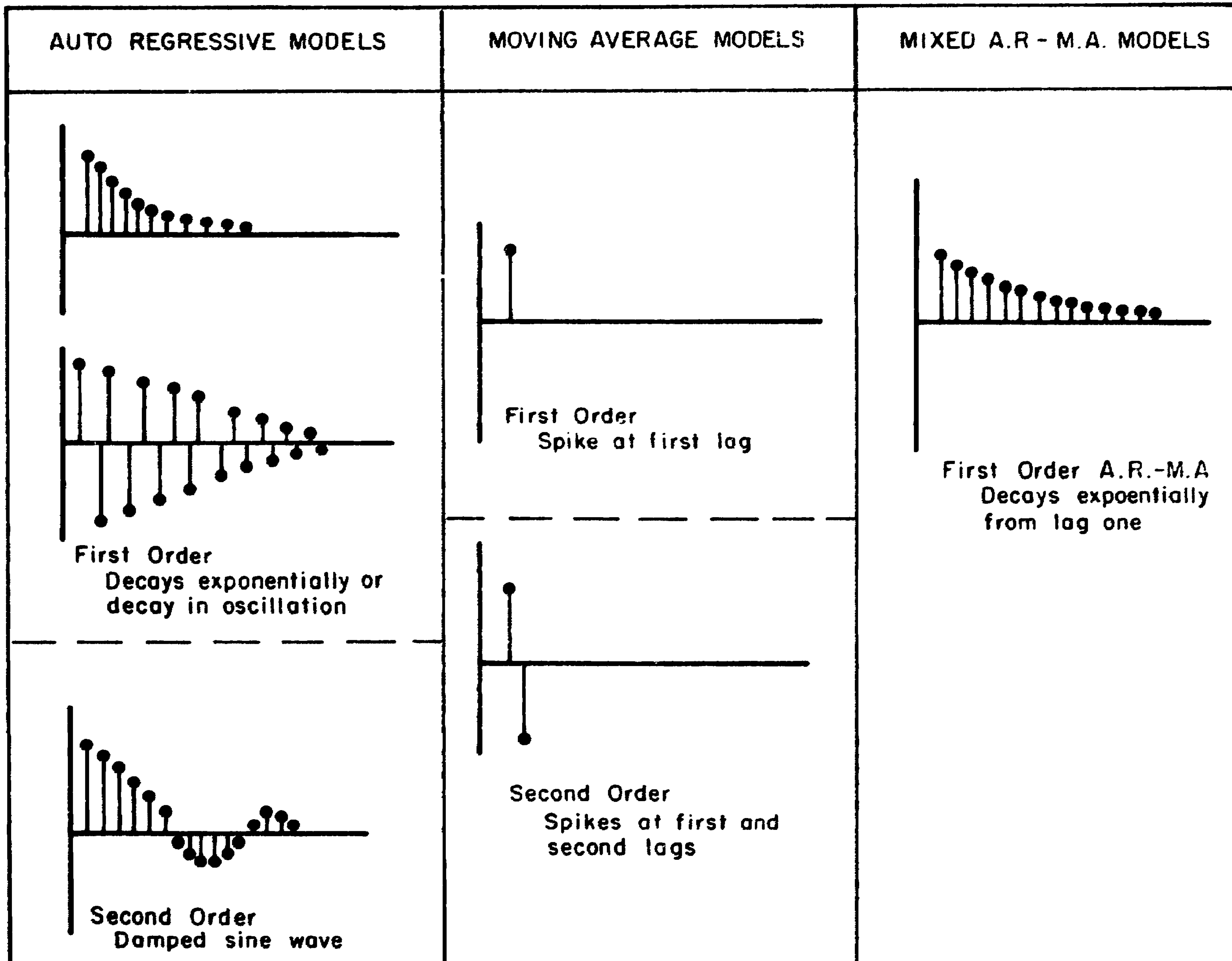
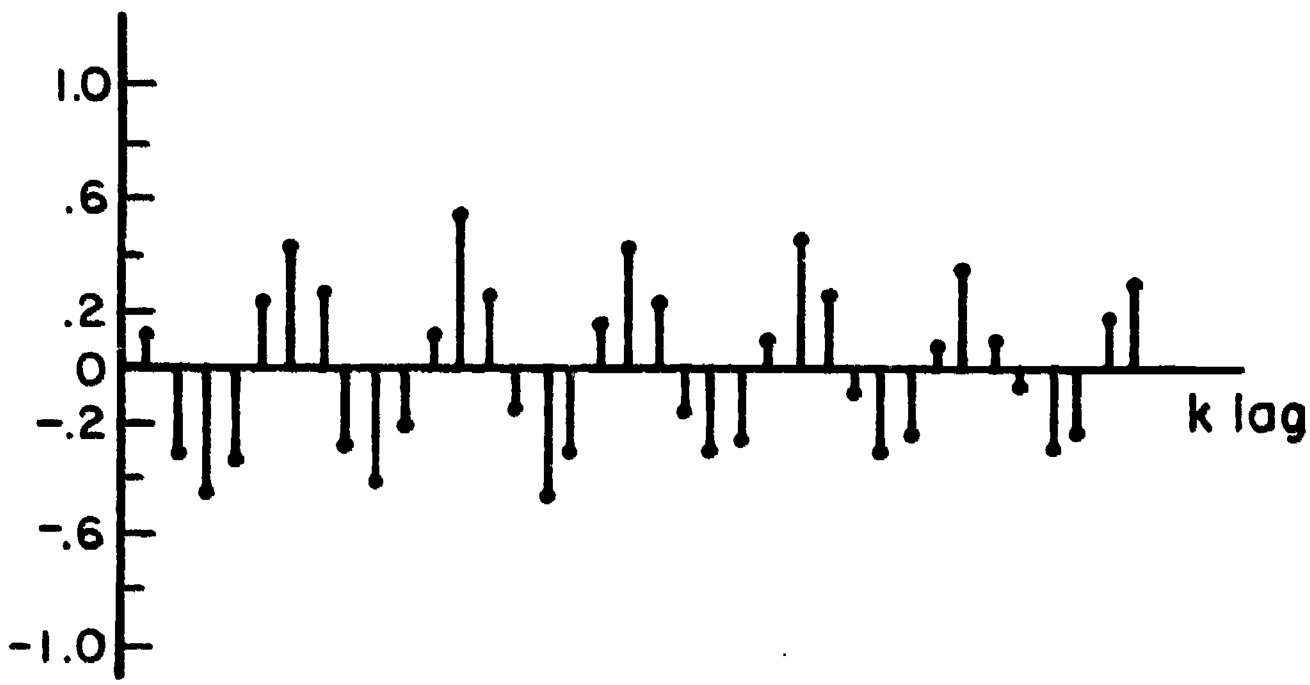


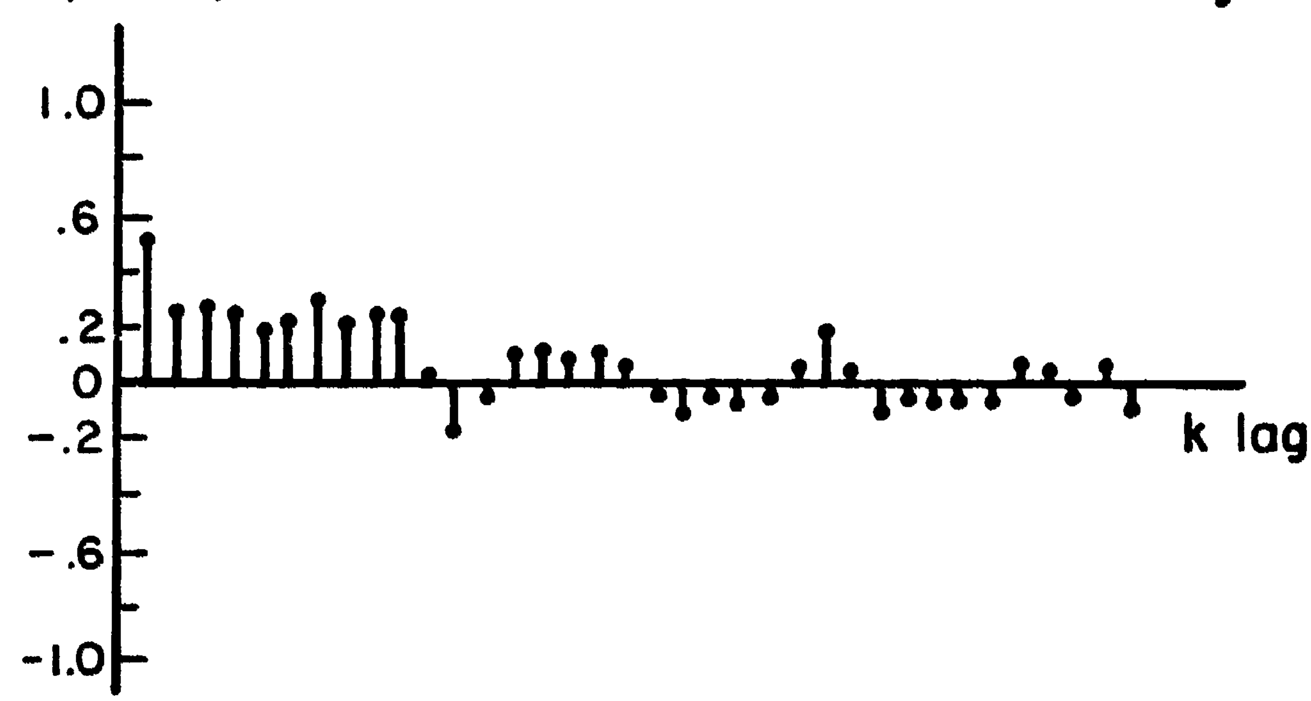
Exhibit 4. Theoretical Autocorrelation Functions

Exhibit 5. CSOE Sample Autocorrelations

a) Sample Autocorrelations : Regular Differencing



b) Sample Autocorrelations: Seasonal Differencing



Estimation:

Once a tentative model has been identified, the unknown parameters (ϕ's and θ's) are estimated by minimizing the sum of squared residuals the (a_t terms) for the tentative model. Computer routines utilizing an iterative non-linear estimation procedure are generally used. Such an algorithm yielded $\hat{\phi}_1 = .479$ and $\hat{\phi}_2 = .256$ for equation (4).

Diagnostic Checking:

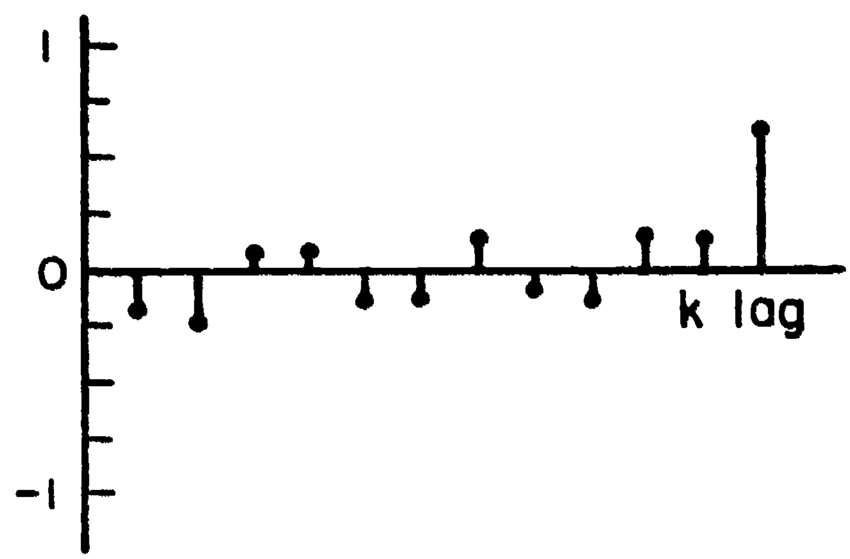
What represents an optimal time series model? One in which all the information which the past might provide about the future is captured. If this is the case and if we have found the optimal model, then whatever forecast errors (differences between actual values and forecast values) remain will be completely independent of prior variable levels or errors. This is true simply because all past information has been captured in our model so forecast errors cannot be related to historic observations. Forecast errors in the model are pure random events!

We can use this concept to diagnostically check the estimated model. In particular, the autocorrelation coefficients between various lags of the forecast errors (a_t) are examined. Provided the model is adequate, these residual errors will be independently distributed with a mean of zero. A portmanteau chi square statistic provides a valuable tool to test this condition [1, pp. 195]. Also, if the a_t values are not appropriately distributed, the pattern of the residual autocorrelation coefficients should indicate the direction of possible model improvement.

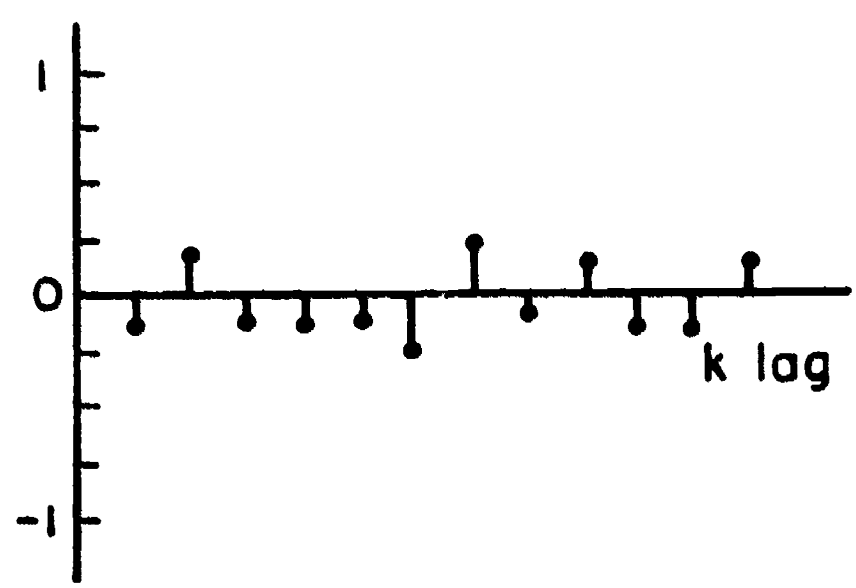
Exhibit 6a contains the residual sample autocorrelation for equation (4). Notice that a large value exists at the twelth lag. The chi square test at 95 per cent confidence level rejects the hypothesis that the model is adequate.

Exhibit 6. CSOE Residual Sample Autocorrelations

a) Residual Sample Autocorrelation for Equation (4)



b) Residual Sample Autocorrelation for Equation (5)



Repeating Identification, Estimation and Diagnostic Checking:

An analysis of the residual sample autocorrelation pattern provides the direction for improvement. A large value at the kth lag indicates the need for a moving average coefficient of order k. As noted Exhibit 6a shows a large value at the twelth lag, indicating the need for a twelth order moving average coefficient. Thus, we have now identified a new model to estimate and diagnosticaly check. The following equation represents the new model.

$$KWH_t = \theta_1 \, KWH_{t-1} + \theta_2 \, KWH_{t-2} - \underbrace{\theta_{12} a_{t-12}}_{\text{new term}} + a_t \qquad (5)$$

The analyst now estimates the coefficients for equation (5). The following values were obtained.

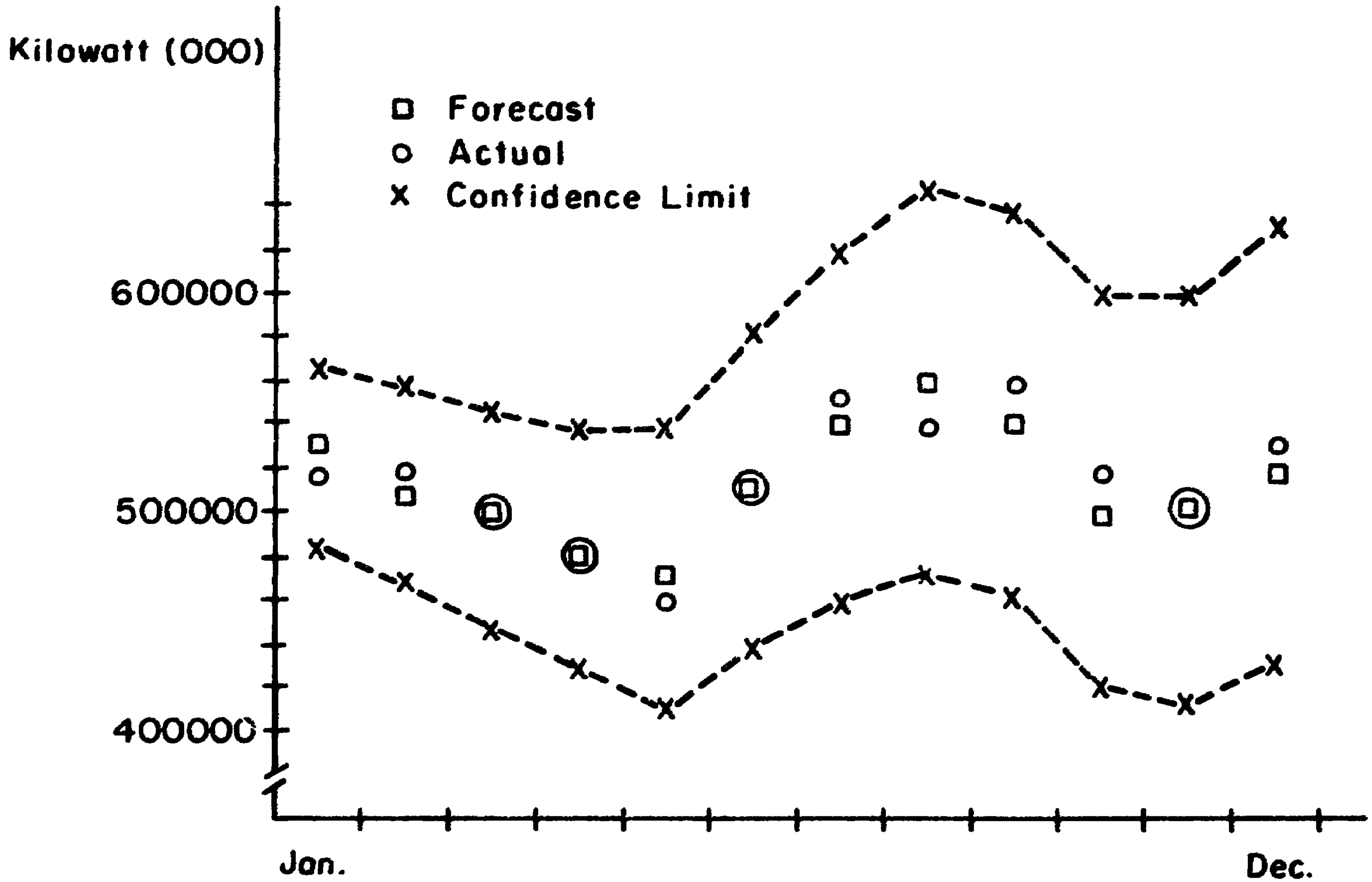
$\hat{\phi}_1 = .643 \qquad \hat{\phi}_2 = .341 \qquad \hat{\theta}_{12} = .645$

Diagnostic checking is repeated, with the sample autocorrelation of the residuals plotted in Exhibit 6b. No large values exist and the chi squate test indicates that equation adequately represents the time series. In general, the analyst would continue to repeat the three steps of identification, estimation, and diagnostic checking until an adequate model is obtained.

Forecasting

With an adequate model selected, the next step would be to forecast future events. In the prior section, the last twelve months of data were withheld from the time series during the identification, estimation, and diagnostic checking steps. Forecasts of these twelve months are made using equation (5) and compared with actual observations in Exhibit 7. The

Exhibit 7. CSOE One Year Forecast



mean absolute percent error for these twelve observations is 2.46%, indicating fairly reliable forecasts. Also depicted in Exhibit 7 are the upper and lower 95% confidence limits of the forecast.

Summary Remarks

There is little doubt that the use of Box-Jenkins methodology as opposed to simple trial and error autoregressive or moving average models will lead to more efficient model development and better forecasting accuracy. This is due to two fundamental reasons: 1) the systematic selection of potential models as opposed to simply pulling model candidates out of the air and 2) the fact that the model allows for all possible combinations of autoregressive and moving average models.

However, a few caveats might be appropriate at this point. First, only a limited amount of research as been conducted, comparing the BJ technique against other methods. The evidence to date does not allow us to draw conclusions on the comparative performance of the BJ approach to other methods [7][8]. The true test of its quality lies in the practitioners use. Second, the educational requirements of the analyst to use this technique are higher than other methods. Yet granting that exponential smoothing is simple relative to BJ, this should not preclude the use of BJ. In fact, an individual with a baccalaureate in industrial engineering could easily handle it's technical requirements.

Finally, the cost of the BJ method is greater than some other methods. Chambers, Murlick, and Smith [3] give a general estimate of $10 for a BJ forecast. Mabert [8] reports that there is a 20-40% increase in personnel time, representing one to four man-hours, and a 5% increase in computer CPU Time (.5 seconds) for the BJ method versus exponential smoothing for

making forecasts.

Yet we honestly believe that in the hands of a qualified analyst, the BJ technique could be a valuable forecasting tool for many business situations. The methodology is appropriate in situations where the variable being studied appears to exhibit basic long run trend with major cyclical and seasonal patterns. Examples would include:

1) deposit levels of a commercial bank
2) sales demands for seasonal "necessary" consumer goods
3) accounts receivable collection rates
4) employee absenteeism
5) machinery breakdowns

This is certainly not an all inclusive listing but simply illustrative of possible usages.

Conclusions

To date, academic literature is replete with various capital budgeting, inventory, receivable, etc. optimization models. But very little attention has been devoted to how an analyst might obtain the forecasts of variables required in such models. In this paper we have presented the basics of a systematic approach to forecasting via time series analysis; Box-Jenkins methodology. The Box-Jenkins methodology is more systematic than the hit and miss tactic prevalent today and, if properly followed, should lead to smaller forecasting errors. The methodology consists of 1) an identification procedure for selecting potential models from a generalized mixed autoregressive-moving average model, 2) the estimation of model parameters and 3) an approach to diagnostically check the models to determine if improvements can be made.

To date, the technique has not been utilized extensively by practicing financial forecasters. This is most likely due to the rather recent development of the methodology. However, it has been shown to be of practical usefulness is a number of empirical academic studies and, hopefully, as practitioners become more knowledgeable of its benefits, the technique will gain more widespread acceptance.

Appendix

The general model proposed by Box and Jenkins can be written as

$$\phi_p(B)Y_t = \Theta_o + \Theta_q(B)a_t \qquad (A.1)$$

where Y_t is a stationary series, i.e., the observations vary about some mean; Θ_o is a deterministic trend constant; the a_t are independent $N(0,\sigma_a^{\ 2})$ shocks, or "white noise;" and $\phi_p(B)$ and $\Theta_q(B)$ are polynomials in B of order p and q respectively where

$$\phi_p(B) = 1 - \phi_1B^1 - \phi_2B^2 - \phi_3B^3 - \dots - \phi_pB^p,$$

and (A.2)

$$\Theta_q(B) = 1 - \Theta_1B^1 - \Theta_2B^2 - \Theta_3B^3 - \dots - \Theta_qB^q$$

where B is a backshift operator such that $BY_t = Y_{t-1}$. The definition of a backshift operator provides a convenient means of noting manipulation of the series. For example

$$\begin{aligned} (1-B)Y_t &= Y_t - Y_{t-1} \\ (1-B-B^2)Y_t &= Y_t - Y_{t-1} - Y_{t-2} \\ (1-B^4)Y_t &= Y_t - Y_{t-4} \end{aligned} \qquad (A.3)$$

As can be seen, the exponent of the backshift operator determines the appropriate amount of backward shifting. $\phi_p(B)$ is called the autoregressive operator and $\Theta_q(B)$ is called the moving average operator. To illustrate, an autoregressive operator such as

$$\phi_2(B) = (1-\phi_1B - \phi_2B^2) \qquad (A.4)$$

can be applied to Y_t and expanded such that

$$(1-\phi_1B-\phi_2B^2)Y_t = Y_t - \phi_1Y_{t-1} - \phi_2Y_{t-2} \qquad (A.5)$$

where ϕ_1 and ϕ_2 are parameters to be estimated. The moving average operator can be applied similarly to the a_t.

The stationary series Y_t may frequently be achieved by appropriate differencing of the original series. It is desirable to transform a non-stationary original series, via regular and seasonal differencing, into a stationary series to allow appropriate identification of a specific model. Thus we may express

$$Y_t = (1-B)^d(1-B^s)^{dl}Z_t \tag{A.6}$$

where Z_t is the original series; d is the number of regular differences; s is the length of the season, such as 12 for a yearly season; and dl is the number of seasonal differences.

By substituting for Y_t in (A.1), the general class of models may be written as

$$\phi_p(B)(1-B)^d(1-B^s)^{dl}Z_t = \Theta_o + \Theta_q(B)a_t \tag{A.7}$$

Such a model is said to be of order (p,d,dl,q).

The general model of (A.7) can be expanded to represent seasonal series. Seasonal autoregressive and moving average operators $\phi_{pl}(B^s)$ and $\Theta_{ql}(B^s)$ and $\Theta_{ql}(B^s)$ can be added so that the general model is of the form

$$\phi_p(B)\phi_{pl}(B^s)(1-B)^d(1-B^s)^{dl}Z_t = \Theta_o + \Theta_q(B)\Theta_{ql}(B^s)a_t \tag{A.8}$$

The seasonal operators are similar to the regular operators described in (A.2).

The sample autocorrelation function is defined as

$$r_k = \sum_{t=1}^{n-k}\left[\frac{(Y_t - \bar{Y})(Y_{t+k} - \bar{Y})}{\sum_{t=1}^{n}(Y_t - \bar{Y})^2}\right] \tag{A.9}$$

where r_k is the sample autocorrelation for lag k, n is the number of observations, and $\bar{Y}$ is the sample mean.

Footnotes

1. For example, see Tiao and Thompson [11] for forecasting applications in telephone call demand, Mabert and Radcliffe [9] for electrical peak load analysis, and Box and Jenkins [1] for stock price forecasts.

2. There is considerable evidence that mechanical, (i.e., quantitative) forecasts are - on the average - as good as, or better, than forecats prepared by "experts." Illustrative of this is an investigation by Elton and Gruber [5] of the accurace of security analysts in forecasting E.P.S. One would generally believe that analysts are experts in their area and should provide reasonably good estimates of earnings. However, they concluded that simple exponential smoothing and autoregressive models were able on average, to project earnings at least as well as analysts.

3. For a clear and concise discussion of the pros and cons of alternative forecasting tools, see Chambers, Mullick and Smith [3].

4. There are occasions when the appropriate differencing patterns are not easily identified. In such a case, the analyst would just have to try various patterns.

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